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Performance Analysis for Virtual-Cell Based CoMP 5G Networks Using Deep Recurrent Neural Nets

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Abstract— Providing high date rates that are independent of user location in the network is one of the Fifth Generation (5G) wireless network goals. This goal becomes even more challenging when the mobility of users is taken into account. The handovers that happens as the user crosses from cell to another can cause a sever degradation in the user's perceived data rate. The concept of Virtual Cell (VC) that is based on Coordinated Multipoint (CoMP) transmission is a promising solution for providing high data rates independent of user location in the network, and in particular for cell edge users. Multiple base-stations (BS) can coordinate with each other creating a Virtual Cell (VC). Users can roam within a Virtual Cell (VC) without the need to perform a handover. This diminishes the number of handovers a user will encounter, and also enhances the data rate for cell edge user by mitigating the Inter-Cell Interference (ICI) within a virtual cell. However, to enable the concept of Virtual Cells (VCs) rapid decisions need to be taken about when to enable / disable the VC mode and which Base Stations should be joining/leaving the VC as the user roams in the network. In this paper, the performance analysis of a novel algorithm based on a modification in the hidden layer of the Recurrent Neural Network (RNN), referred to as Gated Recurrent Units (GRUs). The RNN-GRU model is used for predicting the triggering conditions on enabling / disabling the VC mode. Sequences of the Received Signal Strength (RSS) values for different users in the network, were used for training the RNN-GRU model. After training, the RNN-GRU was used to predict the future RSS values, which is then used for making proactive decisions on enabling/disabling VC mode. **Simulation results demonstrates that the proposed GRU-RNN model achieves an accuracy of 92% to predict the triggering conditions for enabling and disabling the CoMP mode as required based on the mobility of users.**

Index Terms— Coordinated multipoint (CoMP), virtual cell, machine learning (ML), recurrent neural networks (RNN), gated recurrent unit (GRU).

I. INTRODUCTION

The Enhanced Mobile Broadband (eMBB) network is one of the 5G use cases, which has the requirements of very high data rates, that can reach up to 10 Gbps, independent of the user's location in the network (which means providing a uniform user experience across the network) [1]. However, the cell edge users can suffer from a degradation in the perceived throughput due to several factors such as the path loss and the interference from neighboring cells. This degradation could greatly undermine the quality of a real- time applications that requires a very high throughput.

Moreover, as the user moves from one cell to another the handover process is performed in order the maintain the connectivity of the user with the network by associating the user with the cell that has the best signal quality. During the handover process the user will also encounter a degradation in the perceived signal quality due to the delay occurring from performing the handover process. Therefore, maintaining a reliable quality of service as the user roams in the network is a challenging goal in future 5G networks.

Some solutions have been proposed to cope with the degradation in the throughput for the cell edge users. For example, the Inter-Cell Interference Coordination (ICIC) technique [2] which was proposed in Long Term Evolution (LTE), Release 8, and the enhanced ICIC (eICIC) technique proposed [3] in LTE-Advanced (LTE-A), Releases 10 and 11. Although these techniques improve the cell-edge user's throughput, they can result in a degradation in the overall throughput of the system due to the restrictions they enforce on using the radio resources in time and frequency[1].

Alternatively, Coordinated multipoint (CoMP) transmission [4], which was first standardized in Long Term Evolution-Advanced (LTE-A), Releases 11 and 12, allows the association of the user equipment (UE) with multiple BSs (CoMP set). The

[1] There techniques adaptively mute resources that cause strong interference which may result in a degradation in the overall system throughput.

BSs within the CoMP set can coordinate with each other to simultaneously best serve the UE. 5G is expected to further leverage the CoMP technology via creating Virtual-Cells (VCs) [5], which consist of multiple BSs (CoMP set) and the VCs are enabled and adapted according the user's mobility in the network.

The main contribution of this paper is evaluating the performance of a novel algorithm that proactively predicts the optimal triggering conditions for enabling / disabling the VC mode (see Fig.1). The proposed algorithm, which is based on Recurrent Neural Networks (RNNs) and Gated Recurrent Units (GRUs) uses sequences of Received Signal Strength (RSS) values of different mobile nodes for training the RNN-GRU model. Simulation results show that the future RSS values can be proactively and accurately predicted according to the user mobility in the network. Then, decisions on enabling / disabling the VC mode can be made based on the predicted future RSS values.

The reminder of this paper is organized as follows. Section II presents the prior state-of-art on using machine learning (ML) in 5G self-organized networks, Section III discusses the CoMP management based on ML approach using recurrent neural networks (RNN), and Section IV presents the simulation results to show the strength of ML in predicting the future RSS values. In Section V, the performance analysis is shown and discussed. The paper concludes with some remarks in Section VI.

II. Prior State-Of-Art On Using Machine Learning in 5G Self-Organized Networks

In this section we review some of the prior work that has utilized Machine Learning (ML) for predicting the mobility of users in wireless networks. In [6], the authors used a Nonlinear Autoregressive Exogenous Model (NARX) consisting of 12 hidden layers that was trained using the RSS values and the delays between Access Points (APs). The NARX model was able to predict a location which is close to the optimal handover location. The variations in RSS, number of cells with RSS values above a certain threshold and the past handover rate are used in [7] for training the AdaBoost algorithm to predict the incident of handover. The coordinates of the past three visited locations were used in [9] as features for predicting the user's mobility and predicting handovers using a Neural Location Indicator. In [9] the cell IDs of the last four cells a user visited were used for predicting the next cell ID the user is expected to visit in the future. The authors in [10], added the transition time slots to the features used for training the model in [9] to improve the prediction accuracy. However, the obtained accuracy on the next cell predictions was very similar to [9]. Wickramasuriya et al. used sequences of RSS values as features for training a RNN model based on Long Short-Term Memory (LSTM) to predict the next base station (BS) a mobile node will be associated with according to the mobility of users [11]. However, in [11] they did not consider predicting the optimal triggering conditions for enabling/disabling VC according to the user's mobility - which is the goal of our work.

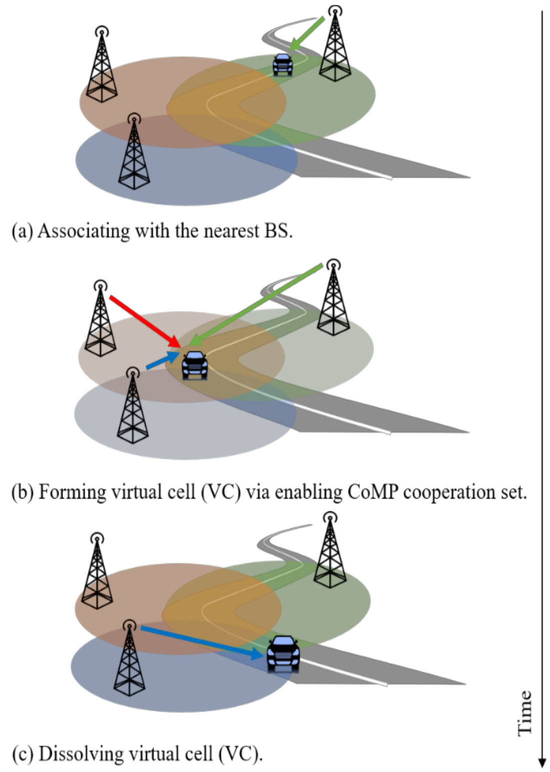


Fig. 1: Adaptively enabling / disabling coordinated multipoint (CoMP) transmission according to the trajectory of user in the network. (a) Associating with the nearest base station (BS). (b) Forming a virtual cell (VC) via enabling CoMP cooperating set. (c) Dissolving a VC.

III. CoMP Management Based On Recurrent Neural Networks

A. System Model

A 6 km × 6 km road network with intersections that are 1 km apart is simulated, as shown in Fig 2. An eight BSs were randomly placed within the road network. Mobile nodes are generated at random locations in the road network with speeds between 8-12 km/h for pedestrians and between 55-65 km/h for vehicles. Intersections are assigned probabilities of 0.5 for going straight ahead, or an equal probability of 0.25 for turning either right or left. Each mobile node in the network will measure the RSS values from the nearest three BSs. The measured RSS values are stored in eight-dimensional vector. The 3GPP path loss model in [12] is used in the system model. This path loss model has an additional term to account for large-scale shadow fading.

$$PL(d) = 128.1 + 37.6 \log(d) + \sigma, \quad (1)$$

Where, d is in kilometers, σ is normally distributed with mean zero and variance 9 dB.

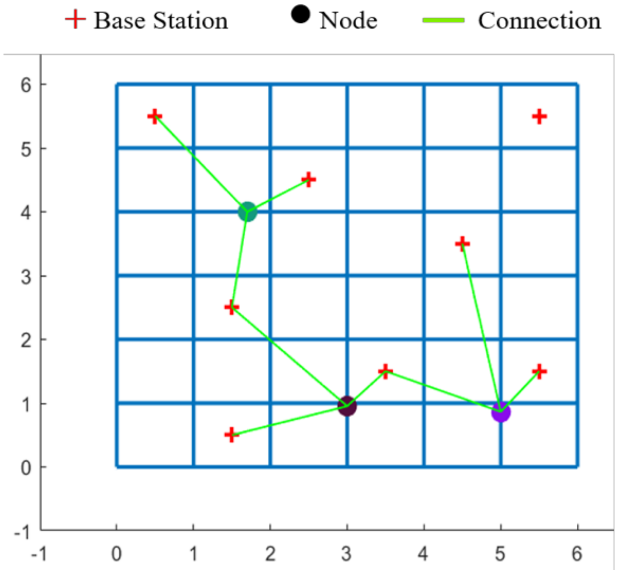


Fig. 2: A road network with eight base stations (BSs) (crosses) and a mobile node (circle). The grid lines are the roads. Each mobile node measures the received signal strength (RSS) from the three closest BSs.

B. Dataset

The dataset used was in the form of an eight-element feature vector, where the positions in the feature vector correspond to the base stations with their RSS values. The RSS values, from the closest Base stations to the mobile node, are stored at their corrosponding locations in the eight-element feature vector and the remaining elements are set (which are the furthest five base stations). As the mobile node moves across the network, the closest three BSs to the mobile node will change, and the RSS values from the closest three base stations will get updated and stored consecutively in a queue data structure. TABLE 1 presents a sample of the RSS data recorded for nine nodes (in rows) in the road network from the eight base stations (in columns).A total of 100,000 sequences of different mobile nodes are collected using this simulation.

TABLE 1: Sample of RSS values for different nodes

BS1	BS2	BS3	BS4	BS5	BS6	BS7	BS8
0.0	0.0	0.0	-88.5	-102.1	-107.8	0.0	0.0
0.0	-83.5	-107.0	0.0	-90.8	0.0	0.0	0.0
0.0	-82.1	- 60.7	0.0	-98.4	0.0	0.0	0.0
0.0	0.0	-95.9	-91.6	-82.5	0.0	0.0.	0.0
0.0	0.0	0.0	-79.5	-82.5	-101.8	0.0	0.0
0.0	-73.5	-117.0	-80.5	0.0	0.0	0.0	0.0
0.0	-85.1	- 90.7	-60.3	0.0	0.0	0.0	0.0
0.0	0.0	-85.9	-81.6	-92.5	0.0	0.0.	0.0
0.0	0.0	0.0	-98.5	-112.1	-105.8	0.0	0.0

C. Recurrent Neural Networks (RNN) - Gated Recurrent Unit (GRU) model

The Recurrent Neural Network (RNN) detects the patterns in sequential information. Unlike conventional Neural Networks (NN), RNNs have a memory which stores information about what happened in all previous time steps for learning a large range of dependencies. The Gated Recurrent Unit (GRU) is a modification to the hidden layer (H) RNN [13], to solve the vanishing gradient problem. The conventional RNN architecture is illustrated in Figure 3. A GRU is made up of two gates, as shown in Figure 4. The first is the update gate, which controls how much of the current cell content should be updated with the new candidate state. The second is the reset gate, which resets the memory of the cell if it is closed. The GRU state equations are [13].

$$\text{reset gate: } \mathbf{r}[\mathrm{t}] = \sigma(\mathbf{W}_{\mathrm{r}}\mathbf{h}[\mathrm{t}-1] + \mathbf{R}_{\mathrm{r}}\mathbf{x}[\mathrm{t}] + \mathbf{b}_{\mathrm{r}}), \quad (2)$$

$$\text{current state: } \mathbf{h}'[\mathrm{t}] = \mathbf{h}[\mathrm{t}-1] \odot \mathbf{r}[\mathrm{t}], \quad (3)$$

$$\text{candidate state: } \mathbf{z}[\mathrm{t}] = \mathrm{g}(\mathbf{W}_{\mathrm{z}}\mathbf{h}'[\mathrm{t}-1] + \mathbf{R}_{\mathrm{z}}\mathbf{x}[\mathrm{t}] + \mathbf{b}_{\mathrm{z}}), \quad (4)$$

$$\text{update gate: } \mathbf{u}[\mathrm{t}] = \sigma(\mathbf{W}_{\mathrm{u}}\mathbf{h}[\mathrm{t}-1] + \mathbf{R}_{\mathrm{u}}\mathbf{x}[\mathrm{t}] + \mathbf{b}_{\mathrm{u}}), \quad (5)$$

$$\text{new state: } \mathbf{h}[\mathrm{t}] = (1-\mathbf{u}[\mathrm{t}]) \odot \mathbf{h}[\mathrm{t}-1] + \mathbf{u}[\mathrm{t}] \odot \mathbf{z}[\mathrm{t}], \quad (6)$$

where, $\mathrm{g}(.)$ is a hyperbolic tangent, σ is the logistic sigmoid[2], $\mathbf{W}_{\mathrm{r}}\mathbf{W}_{\mathrm{z}}\mathbf{W}_{\mathrm{u}}$ are weight matrices, $\mathrm{x}[\mathrm{t}]$ is the input of the RSS values from all eight BSs, $\mathbf{R}_{\mathrm{r}}\mathbf{R}_{\mathrm{z}}\mathbf{R}_{\mathrm{u}}$ are square matrices that define the weights of the recurrent connections, $\mathbf{b}_{\mathrm{r}}\mathbf{b}_{\mathrm{z}}\mathbf{b}_{\mathrm{u}}$ are the bias vectors, and $\odot$ is the Hadamard product.
After constructing the RNN-GRU model, the prediction error is evaluated using the Mean Square Error (MSE) loss function. The loss function, which measures the difference between the true and the predicted RSS values, is defined as follows.

$$\mathrm{MSE} = \mathcal{L}(\mathbf{Y}_{\mathrm{i}}, \widehat{\mathbf{Y}}_{\mathrm{i}}) = \frac{1}{\mathrm{N}} \sum_{\mathrm{i}=1}^{\mathrm{N}} \sum_{\mathrm{t}=1}^{\mathrm{T}} \left(\mathbf{Y}_{\mathrm{i,t}} - \widehat{\mathbf{Y}_{\mathrm{i,t}}}\right)^2$$
$$= \frac{1}{\mathrm{N}} \sum_{\mathrm{i}=1}^{\mathrm{N}} \sum_{\mathrm{t}=1}^{\mathrm{T}} \left(\mathbf{Y}_{\mathrm{i,t}} - \mathbf{H}(\mathbf{X}_{\mathrm{i,t}})\right)^2, \quad (7)$$

[2] The logistic sigmoid is defined as $\sigma = \frac{1}{1+e^{-x}}$

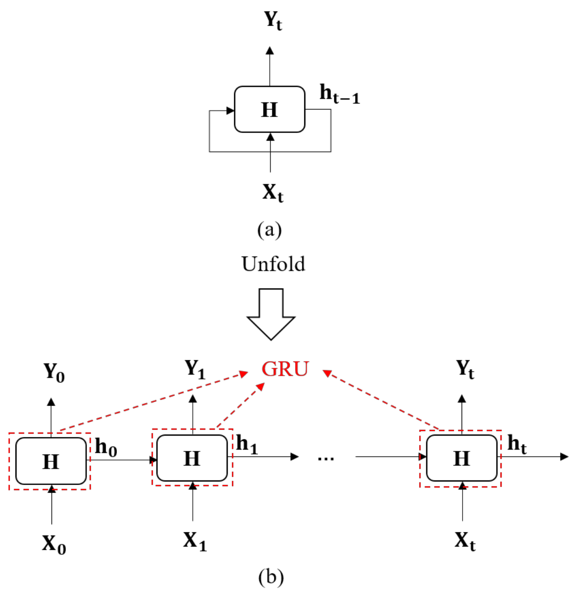


Fig. 3: (a) Th structure of a conventional RNN. (b) The unfolded RNN structure in time when using the GRUs in the hidden layers.

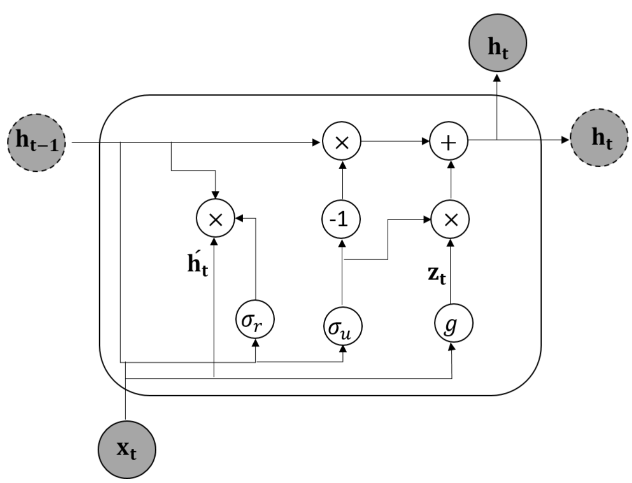


Fig. 4: Gated Recurrent Unit (GRU) architecture. Dark gray circles with a solid line are the variables whose content is exchanged with the input and output of the network. Dark gray circles with a dashed line represent the internal state variables, whose content is exchanged within the cells of the hidden layer. White circles with +, 1 and represent linear operations.

Where N is the number of training examples, $\mathbf{X}_{i,t}$ is the vector of **observed** RSS values from each of the 8 BSs, $\mathbf{Y}_{i,t}$ is the vector of true RSS values and $\widehat{\mathbf{Y}_{i,t}}$ denotes the predicted RSS values (the output of the GRU-RNN model). The purpose of training the GRU-RNN model is to minimize the loss function by choosing a proper weighting matrix $\mathbf{W}$. Thus, the optimization problem can be formulated as follows.

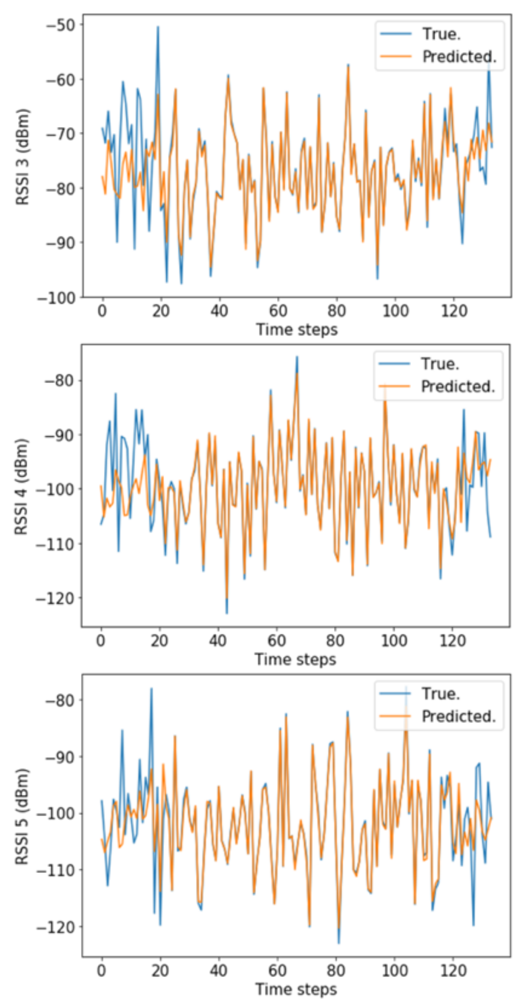
$$\min_{\mathbf{W}} \frac{1}{N} \sum_{i=1}^{N} \sum_{t=1}^{T} \left(\mathbf{Y}_{i,t} - \mathbf{H}(\mathbf{X}_{i,t})\right)^2$$

$$= \min_{\mathbf{W}} \frac{1}{N} \sum_{i=1}^{N} \sum_{t=1}^{T} \left(\mathbf{Y}_{i,t} - \mathbf{W}^{T}\mathbf{X}_{i,t}\right)^2, \quad (8)$$

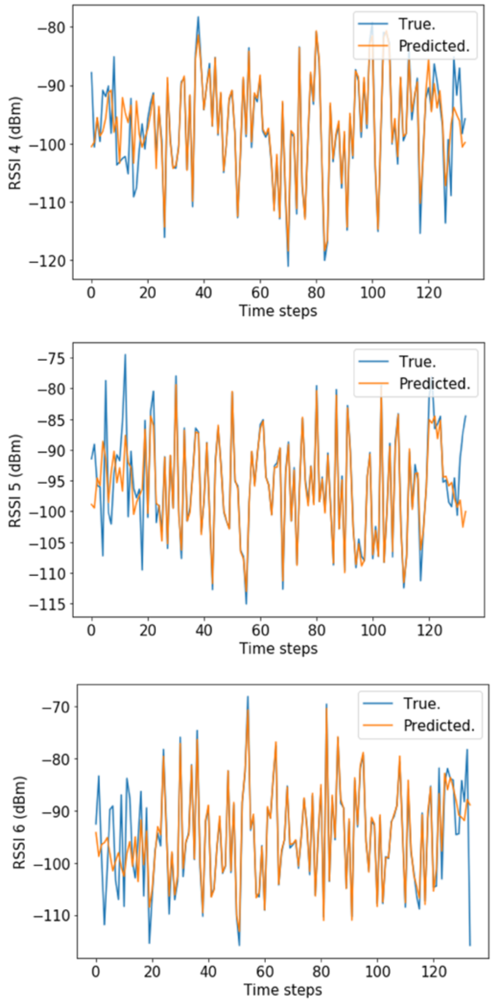
IV. Simulation Results

The RNN-GRU model used in our simulation consists of 512 GRUs. The total of 100,000 sequences that were collected are splitted into 70,000 sequences for training and 30,000 sequences for testing. In Figure 5, it was shown that the predicted RSS values using RNN-GRU model are-close to the true RSS values over the 120 time steps. The network can use the predicted RSS values for making proactive decisions on enabling/ disabling the VC mode to provide a high data rate independent of user's location in the network.

Fig. 6 shows the cumulative distribution function (CDF) of the enabled virtual cells when the GRU-RNN predictive model is applied. Note that the virtual-cell mode is enabled 14 times during the whole duration of time that nodes spend within the network with a probability approximately of 0.95, instead of relying on static virtual cell. Fig. 7 depicts the gradual decrease of the loss function represented in (7) as a function of the number of epochs. It shows that with 75 training epochs, the testing error based on MSE gradually converges.



(a)



(b)

Fig. 5: True versus predicted Received Signal Strength (RSS) values for two different UE. (a) True and predicted RSS values measured from closet three BSs (3, 4 and 5). (b) True and predicted RSS values measured from closet three BSs (4, 5 and 6).

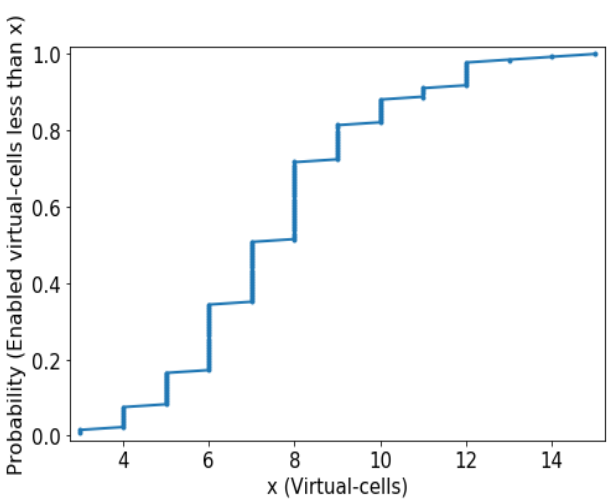


Fig. 6: The CDF of enabling virtual cells using GRU-RNN predictive model.

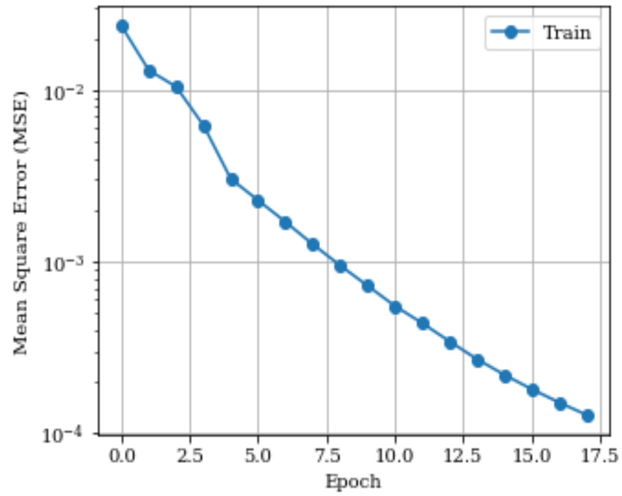


Fig. 7: Convergence of GRU-RNN training model calculated based on Mean Square Error loss function.

V. Performance Anaylisis and Discussion

In this section, the performance of ML-based virtual-cell systems are evaluated in terms of the precision and recall. As illustrated in section IV, for any node in the network, the future RSS values from each of the 8 BSs are predicted using the GRU- RNN model. The predicted RSS values are then used to make cooperative decisions among the BSs for enabling or disabling the virtual cell mode. The process of making proactive decisions about enabling or disabling VC mode becomes a binary classification problem and hence the precision and recall performance measures can be used for evaluating

our model.

A. Precision

The precision is the used to measure the exactness of a classifier. It is calculated by dividing the number of True Positives (TPs) by the number of the True Positives (TPs) and False Positives (FPs). In our system, TP and FP represent the number of true predictions about enabling VC mode and the number of false predictions about enabling VC mode, respectively, for each node in the network. Low precision of the classifier indicates that the classifier enables the VC mode when it's not actually needed, which results in wasting the network resources.

$$\text{Total precision} = \sum_{k=1}^{M} \frac{TP}{TP + FP} \,\% = 86.68\,\%$$

B. Recall

The recall is another performance measure that is used to measure the competence of a classifier. It is calculated by dividing the number of True Positives (TPs) by the number of True Positives (TPs) and the False Negatives (FNs). In our system the number of False Negatives (FNs) represents the number of false predictions about disabling VC mode. The low recall of the classifier indicates that the classifier disables the

VC mode when it is actually needed, resulting in degradation of the quality of signal received by a node.

$$\text{Total recall} = \sum_{k=1}^{M} \frac{TP}{TP + FN}\% \; = 89.71\ \%$$

C. Accuracy

This performance measure is defined as the ratio of decisions made by the correct predictions of enabling /disabling the VC mode to the total number of decisions.

$$\text{Accuracy} = \sum_{k=1}^{M} \frac{TP + TN}{TP + FP + FN + TN}\ \% = \; 92.80\ \%$$

VI. Conclusion

In this paper, the use of Machine Learning (ML) for proactive mobility management in 5G wireless networks is evaluated in a representative scenario. In particular, the performance of the RNN-GRU model is evaluated in predicting the triggering conditions for enabling /disabling the VC mode. The RNN-GRU model was trained using RSS values measured from all the BSs in the network. After the training is complete, the proposed RNN-GRU model was used for predicting the future RSS values, which was then used for making proactive decisions on enabling/disabling VC mode. The proposed algorithm is a promising approach that can achieve the goal of very high date rates independent of the user's location in the network via enabling the use of VCs as needed. Moreover, considering the low latency requirements of the future 5G networks, the proposed algorithm provides rapid proactive mobility management for enabling/ disabling the VC mode.

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